device relative to one or more GNSS satellites of the GNSS positioning system at the respective times that the measurements were captured.

[0017] In one or more implementations, an input to the machine learning model (e.g., or method) may be sets of measurement errors. In this case, measurements may refer to pseudorange and range rate measurements.

[0018] Pseudorange measurements are range measurements plus a time offset corresponding to the difference between the real GNSS time and the GNSS time as estimated by a GNSS receiver, as follows:

Pseudorange=range+clock_offset+range_error

[0019] Range rate measurements are the rate of pseudoranges with respect to time, and include the changes in range due to satellite motion, user motion, and changes in the time estimate (e.g., referred to as clock drift), as follows:

Rangerate=(v_sat−v_user)·(unit vector towards satellite)+clock_drift+range_rate_error

[0020] In this manner, it is possible to form the measurement errors based on the reference position, the known motion of the satellites, and an offline estimate of the receiver clock error, as follows:

Range_error=Pseudorange−range−clock_offset

Rangerate_error=range_rate−·(v_sat−v_user,unit vec towards sat)−clock_drift

[0021] Thus, in one or more implementations, the inputs to the machine learning model may be these pseudorange errors and range rate errors. In order to predict pseudorange errors and range rate errors, values such as azimuth and elevation, a coarse position estimate, and other observed quantities that are made alongside the measurements, such a signal strength (C/NO) and multipath indications may be used.

[0022] In one or more implementations, the machine learning model is generated for local storage on client devices, such that outputs of the locally-stored machine learning model can be used to replace and/or supplement subsequent position estimates (e.g., or estimated measurement errors) provided by the GNSS positioning system, and/or to assist with position estimate determinations for the GNSS positioning system. In this manner, the machine learning model can be used by the GNSS positioning system to compensate for incomplete and/or distorted GNSS signal information, e.g., in the aforementioned challenging signal environments.

[0023] FIG. **1** illustrates an example environment in which an electronic device may use a machine learning model in conjunction with GNSS positioning to estimate device location in accordance with one or more implementations. Not all of the depicted components may be used in all implementations, however, and one or more implementations may include additional or different components than those shown in the figure. Variations in the arrangement and type of the components may be made without departing from the spirit or scope of the claims as set forth herein. Additional components, different components, or fewer components may be provided.

[0024] The environment **100** includes an electronic device **102** and GNSS satellites **104***a*, **104***b*, **104***c* and **104***d* (hereinafter “the GNSS satellites **104***a*-**104***d*”). For explanatory purposes, the environment **100** is illustrated in FIG. **1** as including the one electronic device **102** and the four GNSS satellites **104***a*-**104***d*; however, the environment **100** may include any number of electronic devices and any number of GNSS satellites.

[0025] The electronic device **102** may be, for example, a portable computing device such as a laptop computer, a smartphone, a device embedded in, installed in, and/or coupled to a vehicle, a peripheral device (e.g., a digital camera, headphones), a tablet device, a wearable device such as a smartwatch, a band, and the like, or any other appropriate device that includes, for example, one or more wireless interfaces, such as GNSS radios, WLAN radios, cellular radios, Bluetooth radios, Zigbee radios, near field communication (NFC) radios, and/or other wireless radios. In FIG. **1**, by way of example, the electronic device **102** is depicted as a smartphone. The electronic device **102** may be, and/or may include all or part of, the electronic device discussed below with respect to FIG. **3**, and/or the electronic system discussed below with respect to FIG. **8**.

[0026] In the example of FIG. **1**, the electronic device **102** is held by or otherwise coupled to (e.g., via pocket or strap) a user. However, the electronic device **102** may be coupled to and/or contained within a vehicle. In the example of FIG. **1**, the user is traveling by foot (e.g., walking). However, the user may be traveling within a vehicle (e.g., a land vehicle such as an automobile, a motorcycle, a bicycle, or a watercraft or an aircraft vehicle), through water, e.g. swimming, or by other means.

[0027] In the environment **100**, the electronic device **102** may determine its location based on signals received from GNSS satellites **104***a*-**104***d*. For example, the GNSS satellites **104***a*-**104***d* may be compatible with one or more of the Global Positioning System (GPS), the Globalnaya Navigazionnaya Sputnikovaya Sistema (GLONASS), the Galileo positioning system, and/or generally any positioning system.

[0028] For example, the electronic device **102** may determine its respective location (e.g., longitude, latitude, and altitude/elevation) using signals received from the GNSS satellites **104***a*-**104***d*. As discussed herein, the electronic device **102** may use a machine learning model (e.g., stored in local memory of the electronic device **102**) in conjunction GNSS position estimates (e.g., position estimates determined based on signals received from the GNSS satellites **104***a*-**104***d*) to estimate device location.

[0029] Other positioning technologies (not shown) may be used independent of or in conjunction with GNSS (e.g., the GNSS satellites **104***a*-**104***d*) to determine device location. For example, the location of the electronic device **102** may be determined based on time of arrival, angle of arrival, and/or signal strength of signals received from wireless access points which may have known locations (e.g., within a building or store, mounted on street posts, etc.). Alternatively or in addition, positioning technologies such as, but not limited to, cellular phone signal positioning (e.g., positioning using cellular network and mobile device signals), Bluetooth signal positioning and/or image recognition positioning may be used to determine device location.

[0030] Moreover, the electronic device **102** may implement an inertial navigation system (INS). The INS uses device sensor(s) (e.g., motion sensors such as accelerometers, gyroscope) to calculate device state (e.g., device position, velocity, attitude) and/or user state (e.g., user velocity, position) for supplementing location data provided by the above-mentioned positioning technologies in order to